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How much deforestation in sub-Saharan Africa has been caused by mining?

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Abstract

Sub-Saharan Africa (SSA) has emerged as a prominent destination for mining activities due to its abundant mineral reserves. A key question is understanding the extent to which the establishment and expansion of mines contribute to off-site forest disruptions. We conducted a comparative analysis by examining deforestation within a 1 km to 12 km buffer from the boundary of mines (treatments) “i.e. 1-3 km, 3-6 km, 6-9 km, 9-12 km”, and similar locations without mines (controls) but with comparable environmental characteristics. The rates of annual change were evaluated between treatments and controls, and before and after the establishment of mines from 2001 to 2020. The sampled treatment grids had a total of 6,633,876 hectares of tree cover in year 2000, and lost 17.7% within 2 decades, this was 47.5% higher than the matched controls. Deforestation rates increased by 11,200 hectares annually for mines established between 2009 and 2011 (the median years), relative to pre-creation of mines Our findings emphasize the urgent need for the mining sector to consider their broader offsite environmental costs in their impact assessments, carbon accounting, and associated investments in conservation protection.

Keywords: Biodiversity conservation, Deforestation, Displacement, Leakage, Mining, sub-Saharan Africa.

1.0 | Introduction

Mining activities in sub-Saharan Africa (SSA) have witnessed substantial growth and investment since the early 2000s (Weng et al., 2014), transforming the region into a key player in the global mineral extraction industry. SSA has enormous volumes of high-grade minerals (Edwards et al., 2014a), making it a global epicentre of mine expansion. This financial injection, particularly post-2000, has spurred the establishment of new mines and substantial expansions of existing ones. This culminated in the production of minerals valued at approximately $350 billion in 2018 alone (Yontcheva et al., 2021) . However, the expansion of some of these mines into areas of high biodiversity value poses environmental risks and significant challenges for conservation, especially evident in artisanal gold mining practices (Ahmed et al., 2021; Edwards et al., 2014; Weng et al., 2014). Coupled with the global rise in demand for precious metals, gemstones, and industrial minerals, mining has become a major source of revenue for most countries worldwide and a means of livelihood for local populations (World Bank, 2016).

Mining is not conventionally viewed as a primary cause of direct deforestation, due to its relatively small land footprint (Chakravarty et al., 2011; Ahmed et al, 2021). Mining-induced deforestation and associated habitat fragmentation have been underestimated in some regions (Alvarez-Berrios & Aide, 2015; Sonter et al., 2017), despite evidence from satellite images (Swenson et al., 2011; Asner et al., 2013). This oversight is particularly critical as mining contributes to the loss of intact terrestrial habitats that harbour a hyperdiversity of tropical species (Sonter et al., 2017; Curtis et., al. 2018; Tegegne et al., 2016). This study highlights the overlooked habitat disturbances caused by mining in the SSA region.

The impact of mining extends beyond the immediate mine boundaries, encompassing environmental losses due to deforestation during the construction of mining support infrastructure (such as roads, rails, seaports, and worker settlements) (Edwards et., al. 2014; Haddaway et., al. 2019). These associated infrastructures have caused significant forest loss and fragmentation beyond the sites of mineral extraction (Siquera-Gay et al 2020). Subsequent deforestation near mining settlements for agricultural activities and within-forest impacts via selective logging for timber or fuelwood represent additional 'secondary' impacts of mining. Notably, these secondary impacts can occur in distant forests and intact habitats, as exemplified in the Brazilian Amazon, where mining caused around 1.2 million hectares of deforestation relative to matched controls at distances of 0-70 km away from the boundary of mining leases

(Sonter et al., 2017). Moreover, coal mines in Kalimantan, Indonesian Borneo, induced secondary deforestation up to 50 km from the centre of the mine (Sievernich et al., 2021).

A key unknown is the severity of secondary impacts of mining on deforestation in Sub-Saharan Africa. In this study, the severity of mining-induced forest losses was assessed using a database of 196 mines created post-2000 and a subset of mines (n=45) created in 2009, 2010 and 2011 (median years) in SSA as identified by Ahmed et al. (2021) (Table S2). We deployed a suite of geospatial environmental data and tools combined with statistical matching techniques to tackle two core objectives: **(1)** evaluate the amount of deforestation from 2001 to 2020 in locations with mines (*treatments)* compared to locations without mines (*controls*) at various buffer intervals; and **(2)** compare the annual rates of deforestation before and after mine creation (i.e., across time) with distance from mine (i.e., across space).

This study underscores the critical need for informed and proactive approaches to address the multifaceted impacts of mining on forests and biodiversity. As governments, researchers, and stakeholders grapple with the intricate challenges posed by mining activities, this research provides valuable insights that can inform policy, conservation strategies, and sustainable development initiatives. The study prompts a re-evaluation of existing decision-making frameworks to ensure they comprehensively account for both primary and secondary impacts of mining, fostering a more holistic and environmentally conscious approach to mining practices in SSA and beyond.

2.0 | Materials and Methods

2.1 | *Study Region*

This study covers sub-Saharan Africa (SSA), with prominence on the Afrotropic region which comprises four ecological zones (ecozones): the tropical rainforest , tropical moist deciduous forest , tropical dry forest , and tropical shrubland . These ecozones cover 64% of SSA's land area (FAO, 2016) (Fig. 1). The region is endowed with the largest mineral reserves and deposits globally (Edwards et al., 2014a), such as bauxite, gold, copper, diamond, limestone, and iron-ore. SSA has a population of ~1.1 billion (World Bank, 2021), and is faced with political and socio-economic challenges including armed conflicts and environmental degradation, which has made it one of the most economically impoverished regions globally (IMF, 2021).

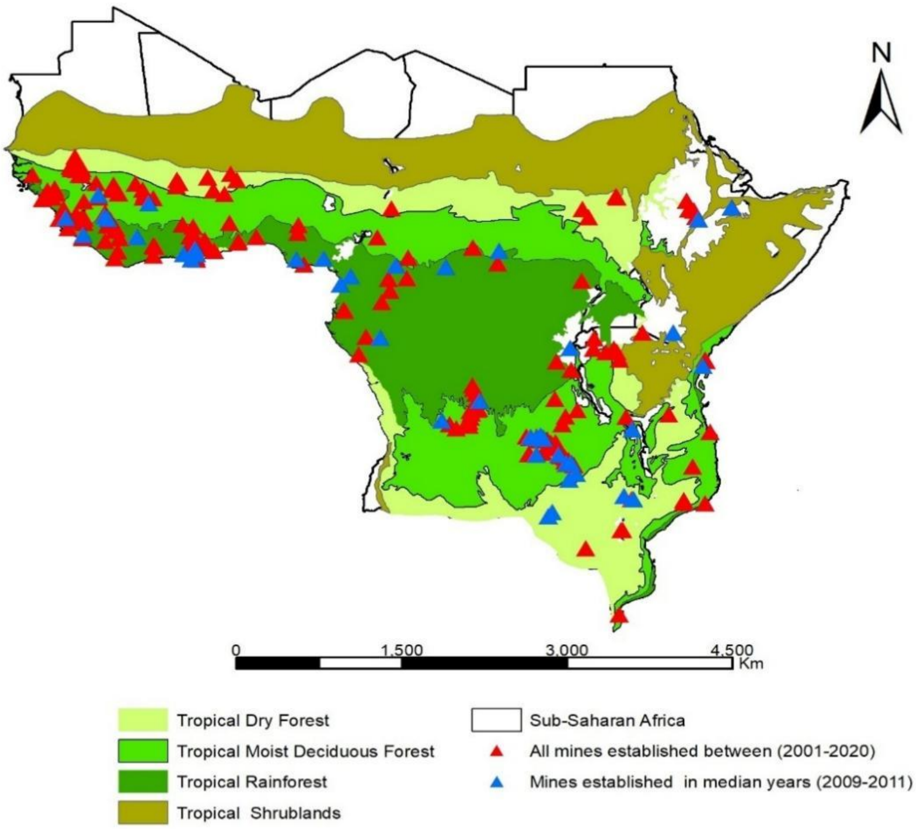

Figure 1. Map of the study area showing mines established between 2001- 2020 in red triangles and the subset of mines established in the median years between 2009-2011 in blue triangles (Ahmed et al 2021), and the ecological zones of sub-Saharan Africa; tropical rainforest, tropical moist deciduous forest, tropical dry forest and the tropical shrublands (FAO, 2016).

2.2 | *Forest and deforestation in sub-Saharan Africa*

Forest - The most common definition of forest used in many countries of SSA is an area of >0.5 ha with >30% canopy cover of trees at >5 m height, or trees with potential to grow to these thresholds (FAO, 2016). Forests may thus include natural primary habitats and secondary habitats consisting of newly planted trees, naturally regenerating forests, and forestry plantations.

Deforestation - Hosonuma et al. (2012) depicted deforestation as the conversion from forest into other land uses, thereby assuming that the forest is not anticipated to regrow without artificial means. In this study, deforestation follows the definition of Hansen et al (2013):

"Forest loss as a stand-replacement disturbance or the complete removal of tree cover canopy at the Landsat pixel scale".

2.3 | *Data and Broad Approach*

To evaluate the effect of mining on environmental losses in the study area, the counterfactual scenario was assessed by comparing deforestation around locations with mines versus those without mines. We focused on mines utilizing open-pit and quarrying extraction methods. Therefore, we utilized the open-access, high-resolution 21st-Century Global Forest Change (GFC) dataset (Hansen et al. 2013), which comprises various forest layers, i.e., *tree cover 2000, loss year, loss,* and *gain*. The dataset was used to extract the tree cover statistics for the baseline year at 30% canopy threshold, the *loss* and *loss year* layers were also used to extract the annual forest cover loss statistics from 2001 to 2020. The GFC is a product of the Landsat imageries with medium spatial resolution (30 metres) and suitable temporal resolution, it is suitable for measuring tropical deforestation (Galiatsatos et al., 2020).

Mines established post 2000 within the forested areas of SSA from Ahmed et al. (2021) were used to generate four buffer zones of 3 km width around each mine, originating from 1 km away from the mines' boundaries (i.e., 1-3 km, 3-6 km, 6-9 km, and 9-12 km). The choice for multiple buffer zones was to capture the potential impacts of mining within the forested areas at various distances. This approach allows for a more precise assessment of how the impact of mining on deforestation varies with proximity to the mines. We generated a 2 by 2 km grid-squares covering the entire forested area of the study region, we defined the treatment squares as grid-squares that are within 1- 12 km from the boundary of the mines (*n=196*). We excluded grid-squares that were within a distance of 12-30 km from the mines boundary, this was to avoid overlapping and interference within treatments and controls. This resulted in a total of 38,500 square-grids for the 196 treatment locations within the 4 buffer zones covering the entire study area.

2.4 | *Matching Analysis.*

Matching statistical techniques were employed to assess the impact of having a mine near to a forest on the extent and rate of deforestation. The main objective was to compare the amount of forest loss between the treatment locations and matched control locations. Matching was used because of its ability to eliminate bias in the selection and pairing of treatment and control units (Andam et al., 2008) and is suitable in balancing covariates (Ho et al., 2011). It is widely applied in the assessment of causal inference (Stuart, 2010) and in conservation studies

(Schleicher et al., 2019). The matching analysis was used to identify grid-squares within control buffers that closely resemble those within the treatment locations in terms of key environmental characteristics that could potentially affect deforestation. Matching studies of deforestation typically adopt this approach, as it allows for a more rigorous assessment of the causal effects of deforestation (Braber et. al., 2018; Sonter at al., 2017). To accomplish this, we carefully selected appropriate variables for use in the matching process from the known drivers of deforestation of relevance to this study (Table S1). By matching treatment and control locations based on these key variables, the study aims to create comparable groups that differ only in terms of the presence or absence of mines nearby. In controlling for key factors through the matching process, we were able to isolate and attribute any observed differences in forest loss to the presence of nearby mines. Previous studies have shown some of the variables that are likely to influence forest disruptions are categorised into the following: (i) Geographic Characteristics; (ii) Land Use and Land Cover; (iii) Socioeconomic Factors; (iv) Environmental Factors; and (v) Political and Institutional Factors (Curtis et al., 2018; Ferretti-Gallon & Busch, 2014; Lievano-Latorre et al.2021).

2.4.1 | *Matching Variables.*

Based on previous research, the variable selection process is done best without using the observed outcomes (Andam et al., 2008; Braber et. al., 2018; Sonter et al., 2017). Therefore, the following variables were selected based on their suitability in assessing the impact of mining on the forest: (a) *elevation* derived from the digital elevation data (DEM) at 225 m spatial resolution (GMTED2010); (b) *vegetation cover* from the vegetation continuous fields (VCF) for the year 2000 at 250 m spatial resolution from MODIS (DiMiceli et. al., 2015); (c) *population density,* using the 1 km Gridded Population of the world Density (CIESIN, 2018); (d) *topographic positioning index* (TPI) (Weiss 2001) and (e) *topographic wetness index* (TWI) (Kopecky et al 2021), both indices were derived from the digital elevation data using QGIS (QGIS 2022).

Control locations - By carefully selecting control locations that are as similar as possible to treatment locations, we can better isolate the effects of mining on deforestation and draw more reliable inferences about its impact. To achieve this, we used the grid-squares of 2 x 2 km covering the entire ecological zones of SSA, similar to the method used by Lievano-Latorre et al. (2021). To prevent overlap between treatment and control locations and ensure a clear distinction, we excluded any grid-square whose boundaries were less than 30 km away from the treatments. This step was crucial to avoid any potential spillover effects of mining activities that could affect nearby control locations (fig. 2).

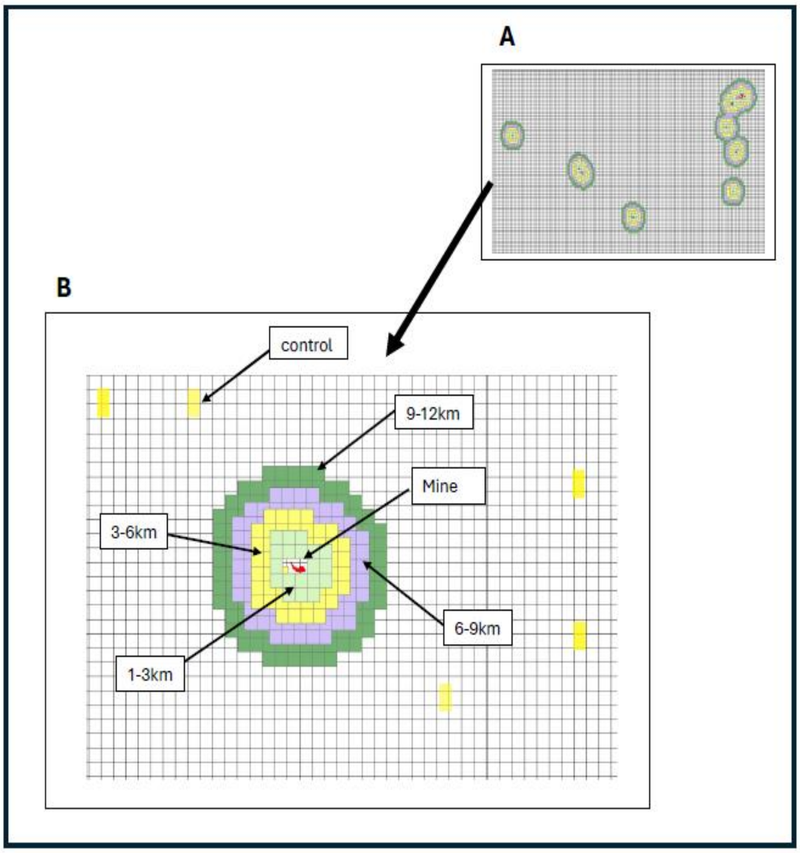

Figure 2. Map of the study region showing mine in red and the grid-squares used in the matching of controls and treatments at various buffers (mint=1-3 km buffer, light yellow=3-6 km buffer, purple= 6-9 km buffer and green = 9- 12 km buffer). The dark yellow grids far from the mines are the controls.

This selection process followed the approach outlined by Devenish et al. (2022) and Lievano-Latorre et al. (2021), ensuring that control locations were as similar as possible to treatment locations in terms of environmental and geographical characteristics. By doing so, we aimed to create a robust framework for assessing the specific impacts of mining on deforestation. A subset of control locations was created for each country, to ensure unbiased results and eliminate the possibility of incorrectly matching treatment and control locations across national boundaries. Country-specific matching was performed, by pairing the matched treatments and controls that fall within the same country, because mining and habitat protection laws and regulations vary between countries in SSA.

Several matching algorithms were applied using the *Matchit* package in R (Ho et al., 2011). Considering the skewness in the ratio of controls to treatments (>80:1) in the data, it became imperative to choose a matching method that maximizes the use of abundant control group while ensuring that matches are close in terms of covariates. Therefore, we adopted the *Nearest Neighbour* matching method which ensures that the best matched controls are utilized for each treatment unit and improves the balance between the groups. Matching without replacement yielded the best results and better covariate balances compared to other approaches (Stuart, 2010; Ho et al., 2007). We matched treatments and controls grid-squares of similar biophysical and social characteristics (matching variables) (Table S1). The amount of deforestation over time was compared between the treatments and their corresponding matched controls. Propensity scores matching (PSM) was used to facilitate the construction of matched sets with similar distributions and summarised all the variables into one scalar grouping of individuals with similar scores (Rosenbaum and Rubin,1983; Stuart, 2010).

$$\text{Propensity score: } [P(X) = \Pr\,(d=1|X)] \qquad (1)$$

Where *P* indicates the Propensity score, *X* is the covariate value, Pr is the probability and *d* is the unit in the *treatment and control* groups.

Assessing the balance of matching - The quality of outputs from the matching analysis were checked using the covariate balance in the *cobalt* package in R (Greifer, 2021). We diagnosed the balance using the standardized mean differences (SMD) as suggested by Schleicher et al., (2019) and Stuart (2010). A better balance with few large numbers will yield less bias in treatment effect estimates (Figure S1); SMD values of < 0.25 were used as acceptable balance for treatments and controls (Stuart et al., 2013).

$$\text{SMD} = \frac{\underline{X}_1 - \underline{X}_2}{\sqrt[2]{(S_1^2+S_2^2)/2}} \qquad (2)$$

Where $\bar{X}_1$ and $\bar{X}_2$ are sample means, while S_1^2 and S_2^2 are sample variance for both the treatments and controls.

2.4.1 | *Post Matching*

The matched treatment and control grid-squares (n= 77000) were used to extract tree cover for the year 2000 and annual forest losses (2001-2020) at various buffer distances over time. In addition, we calculated the changes in the annual rates of deforestation after mine establishment within the treatment areas.

2.5 | *Comparative analysis of the influence of mining on cumulative deforestation in treatment versus control locations across different time periods and within various buffers.*

We assessed the cumulative deforestation within the treatment and control locations over time using the grid-squares generated from the boundary of the buffers at intervals of 3km for distances of 1 to 12 km, with the hypothesis that control locations are unaffected by mining activities as indicated by Sonter et al (2017). The *Google Earth Engine* (GEE) open-source tool was utilised to extract the data for both the tree cover for the baseline year $[T_c(0)]$, and the annual forest loss $[T_c(0) - T_c(n_{\text{-year}})]$ from 2001 to 2020. This data extraction was performed for individual matched treatment and control cells within each buffer, The tree canopy cover threshold of 30% was adopted as the average for the study area (FAO, 2010) to balance the disparity in national forest definitions by the various countries in the SSA region, and to eliminate non-relevant grid-squares. We assessed the normality of the data and obtained a p-value < 0.05 for both control and treatment locations, indicating that the data is not normally distributed. Mann-Whitney U test was used to evaluate the difference in forest loss between the control and the treatment locations.

Additionally, we performed a supplementary analysis using a subset of 45 mines established during the median years of the study (2009, 2010, and 2011) (Figure 1). The subset facilitated a comprehensive examination of the data covering approximately 10 years before and after mine creation. Furthermore, we delved into the spatial dynamics of the impact of mining by considering various buffers around the mining sites. This was aimed to elucidate patterns and variations in cumulative deforestation, providing valuable insights into the long-term environmental consequences of mining operations in distinct spatial contexts.

2.6 | *Changes in the rate of deforestation before and after the establishment of the mine (across time) in relation to distance from the mine (across space).*

To evaluate how the rate of deforestation varied across both time and space, we examined the extent of deforestation in treatment locations compared to their matched control locations. Specifically, we focussed the analysis on designated buffer zones surrounding the mines (1-3 km, 3-6 km, 6-9 km, 9-12 km) and compared deforestation rates to matched control areas to determine the relative impacts. To make valid comparisons regarding deforestation over time in relation to the mine, yearly deforestation rates were normalised based on the number of years since mine creation. To account for differences in initial forest cover, we considered the deforestation rates as a proportion of initial forest cover. Mines that were less than 4 years old were excluded from the analysis due to inherent limitations associated with sparse data. To overcome this constraint, we performed a supplementary analysis using mines established during the median years of the study (2009, 2010, and 2011) resulting in a subset of 45 mines. The subset facilitated a comprehensive examination of the data covering approximately 10 years before and after mine creation; Mfc (-5, 0, +5,+10), thereby generating a better understanding of whether deforestation rates experienced a significant increase after the creation of the mines. Statistical assessment of the observed differences between the two data groups (before and after mine creation) was conducted using a Mann-Whitney U test, applying a significance threshold of p-value < 0.05.

Regression model (Generalized additive model)

As a response variable we analysed the the proportion of initial forest cover that underwent deforestation relative to control areas ($p^*_{m,t,b}$) which we define as;

If $F_{m,t,b}$ and $D_{m,t,b}$ are the area of forest (ha) and amount deforestation (ha) at mine $\boldsymbol{m}$, at time $\boldsymbol{t}$ within buffer ring $\boldsymbol{b}$, respectively. Then, the cumulative proportion deforested at time t can be expressed as:

$$P_{m,t,b} = \frac{\sum_0^t D_{m,t,b}}{F_{m,0,b}} \tag{3}$$

Where $t=0$ is the time at the start of the data (i.e. the year 2000)

To analyse how the proportion deforested varied between treatment and control at different distances from the mine at different times since mine establishment, we fit GAM models to the proportion deforested relative to the control, $p^*_{m,t,b} = p_{m,t,b} - p^c_{m,t,b}$, where p^c is the proportion deforested in the matched control cells. We included a thin plate spline smooth function for years since mine creation as a predictor variable and to account for pseudoreplication we also included Mine ID as a random effect. A model was fit for each buffer zone (1-3 km, 3-6 km, 6-9 km, 9-12 km) and model fits were extracted at various time periods before and after mine creation Mfc (-5, 0, +5,+10) to evaluate how deforestation rates progress through the establishment of a mine and beyond.

3.0 | Results

3.1 | *Impacts of mining on cumulative deforestation in treatment versus control locations.*

Over the span of two decades, there was a cumulative forest cover loss of 2,401,777 hectares within the sampled grid squares around the matched treatment and control locations (n=77,000). Specifically, within the treatment grid-squares, there was a cumulative deforestation of 1,171,794 hectares, constituting 17.7% of the total tree cover within the sampled treatment grid-squares in year 2000 (Figure 3A). In contrast, the control grid-squares, experienced a cumulative forest loss of 12% of the tree cover in 2000. The findings indicate a significant higher net deforestation in the treatment locations compared to their matched controls ($W = 22216$, p-value < 0.01). The average rate of deforestation per grid-square in the treatment locations was 32 hectares and 31 hectares in the matched control locations (Figure 3A).

Considering the 45 mines established during the median years of our study, the average annual deforestation rate per sampled treatment grid-square from year of mine creation until 2020 was 145 hectares (Figure 3B). In contrast, control locations exhibited an average deforestation of 142 hectares per year.

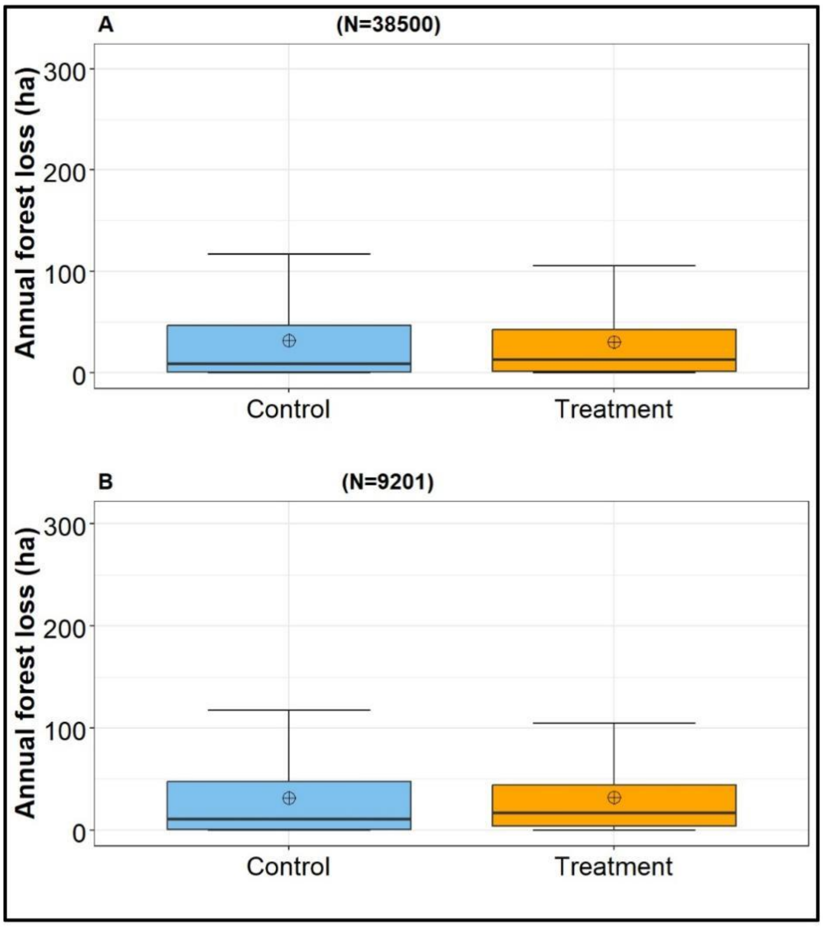

Figure 3. The impacts of mines on deforestation within treatments and controls in sub-Saharan Africa from 2001 to 2020. (**A**) Mean and median forest loss for all mines created between 2001- 2020 and their matched controls. (**B)** Mean and median forest loss for the subset analysis of mines created 2009-2011. Box plots show mean (crossed dot), median (bold line), upper and lower whiskers show the minimum and maximum values. To improve visualisation, outliers in the data are not shown.

3.1.1 | Proportion of initial forest cover deforested within buffers (*n=196*). At five years before mine creation [$M_{fc}(-5)$], the proportion of initial forest cover deforested was -0.2%, 0%, -0.1% and 0% at the 1-3 km, 3-6 km, 6-9 km and 9-12 km buffers, respectively (Figure 4A). At mine creation [$M_{fc}(0)$], the proportion of deforestation increased to 3.5 % at the 1-3 km buffer, and gradually decreasing to -1% within the 9-12 km buffer (Figure 4B).

Five years post-mine creation [$M_{fc}(+5)$], deforestation rates were higher, with proportions of 13.5%, observed within 1-3 km, buffer. Subsequently, deforestation diminished, with a 1% rate within the 3-6 km buffer, and stabilized to below 1% up to the 9-12 km buffer (Figure 4C). At 10 years post-mine creation [$M_{fc}(+10)$], the proportion of initial forest cover deforested was

15% within the 1-3 km buffer and 3% within the 3-6 km buffer. The deforestation rates remained constant at <1% from the 6-9 km and 9-12 km buffer (Figure 4D).

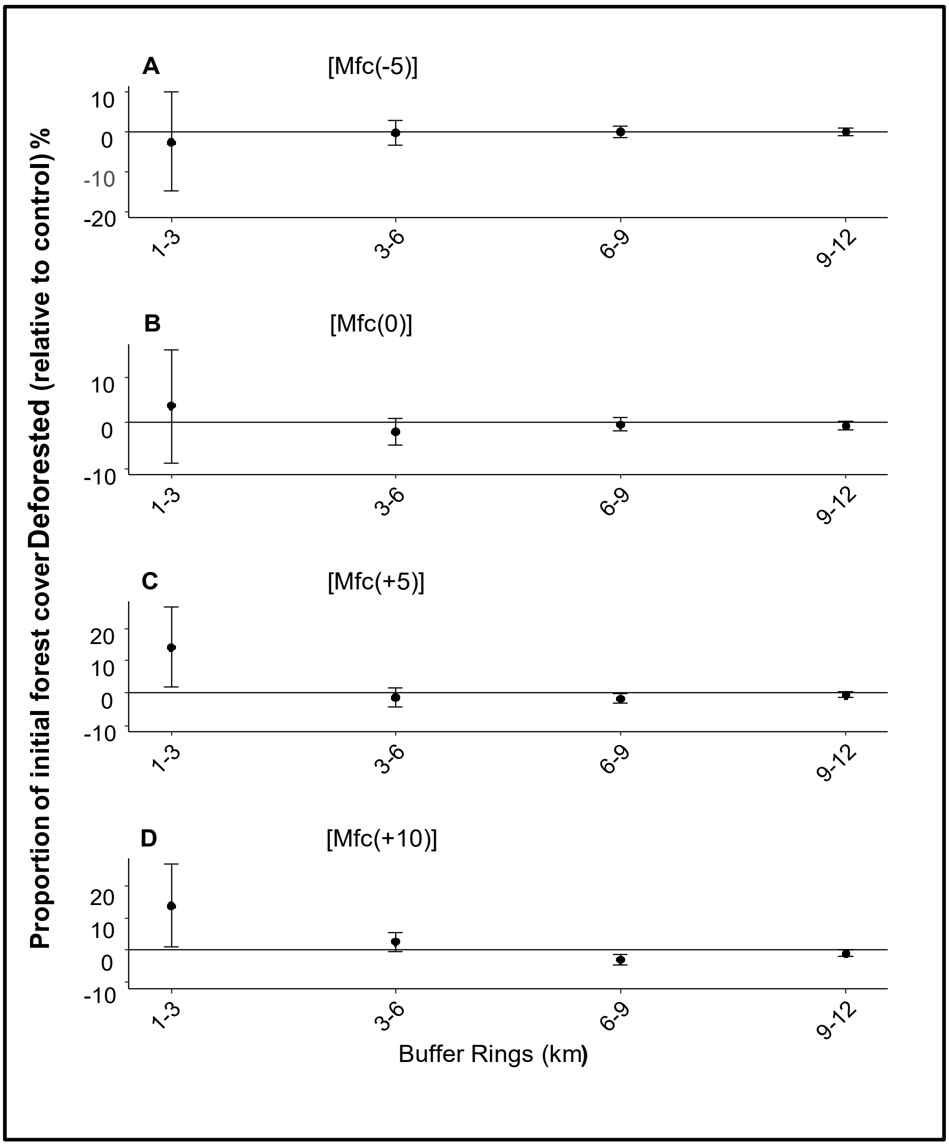

Figure 4. **Proportion of initial forest cover deforested relative to control (*%*) (*n=196*).** Plots from the GAM regression within the 1-3 km, 3-6 km, 6-3 km and 9-12 km buffer in SSA from 2001 to 2020. (**A**) 5 years pre-mine creation, (**B**) at the year of creation, (**C**) 5 years post-mine creation, and (**D**) 10 years post-mine creation. The error bars represent the 95% confidence intervals of the estimated proportion of initial forest cover loss (derived from the

upper and lower CIs of the buffer), the black line marks the reference points, and the values below zero indicate a negative forest cover loss/ change (i.e., forest gain).

3.2 | *Changes in deforestation rate before and after the mine creation (i.e., across time).*

After the establishment of mines, there was a significant and statistically meaningful increase in deforestation rates. Before mines were created, the average annual deforestation rate was 1,665 hectares. However, following the creation of the mines, this rate more than doubled to 4,314 hectares (Figure 5A; p-value < 0.01).

The supplementary analysis conducted on the subset of mines created during the median years of the study (n=45) indicated that the average annual deforestation in the treatment locations before mine creation was 1,572 hectares, whereas it increased significantly to an average of 4,972 hectares after mine creation (Figure 5B; p-value < 0.01). Here, our results show that the creation of mines led to a higher level of deforestation in the treatment locations.

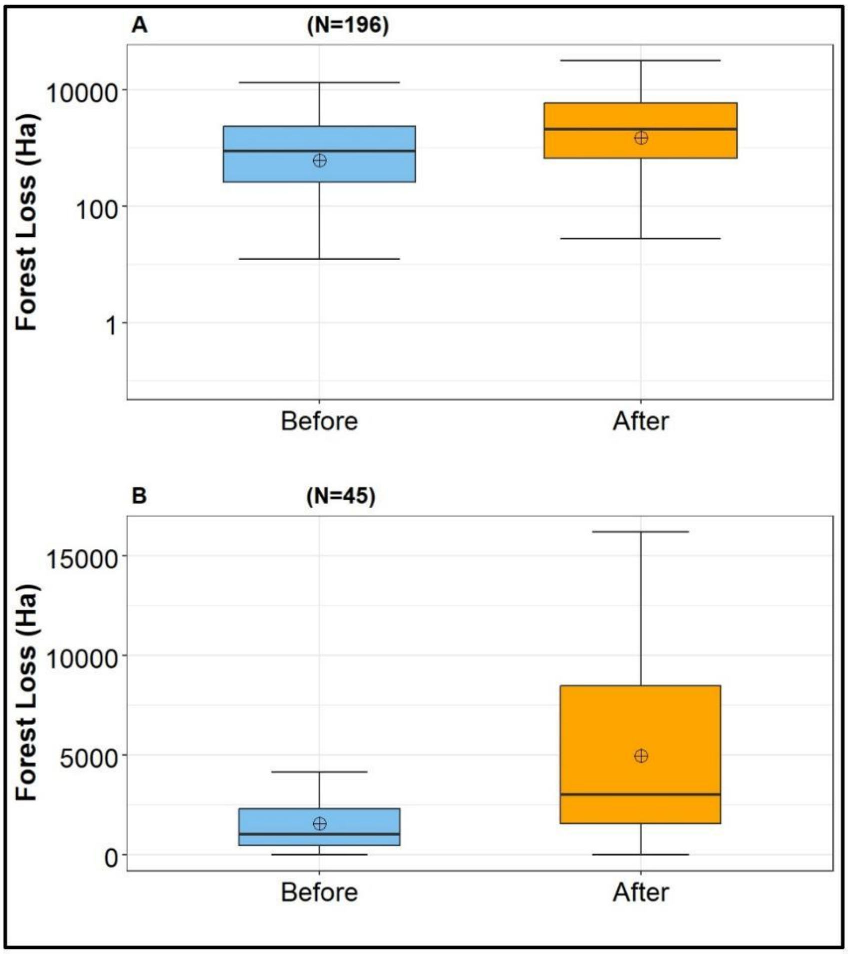

Figure 5. Change in rates of deforestation before and after the mine creation. Plots showing the difference in the annual mean rates of deforestation before and after the creation of mines in SSA from 2001 to 2020. The metrics calculated were the rates of deforestation before and after mine creation. **(A)** Analyses for all the mines (*n=196*), and **(B)** the subset of the mines (*n=45*) created at the median years of the study. Box plots show mean (crossed dot), Median (bold line), upper and lower whiskers show the minimum and maximum values. Outliers in data are not shown.

4.0 | Discussion

The mining industry in sub-Saharan Africa (SSA) attracted huge investments since 2000 and increased immensely after the 2008 global financial crisis (Alvarez-Berrios & Mitchell Aide, 2015), producing minerals worth $350 billion in 2018 alone (Yontcheva et al., 2021). This study compared the secondary effect of mining on deforestation in SSA by matching treatments versus controls and analysing the rates of loss before and after the creation of mines within two decades. On average, there was at least 47.5% extra deforestation in the sampled treatment grid-squares compared to the matched control locations. This emphasizes the imperative for the mining sector and policy makers to consider the broader environmental implications of mineral extraction in licensing, impact assessments, carbon accounting, and associated investments in conservation protection.

4.1 | *Impacts of mine expansion on forest conservation*

The annual average deforestation rate in the treatment locations increased by 160% to 4,314 ha post-mine creation from an average of 1,665-ha pre-mine creation. However, we also observed some significant differences in deforestation rates across our data. In summary, more than 20 mine locations recorded an increase of over 80% in their annual deforestation rates nine years after the creation of the mine, compared to the nine years before the mine's creation. This supports an analysis by the World Bank (Johnson & John, 2019) that revealed regional deforestation has increased significantly post mine creation in areas with mines.

Significant forest losses, and changes in forest cover throughout Central Africa mirrors the levels and impacts of mining on forest loss observed by Sonter et al (2017) in the Amazon. The proportion of forest loss 5 years pre-mine creation ranged between -2% to 0% across all buffers similar to the trend recorded in the Democratic Republic of Congo (DRC) from 2005-2010 (Potapov et al., 2012). However, we found that these rates changed drastically after mine creation. Within the 1-3km km buffer, the proportion of loss was 13.5% and 17% at 5- and 10-years post-mine creation, respectively, with the surge in deforestation especially severe for mines created after 2008, and the 2010 peak deforestation in the DRC (Turubanova et al., 2018). Deforestation dropped to about 3% at the 9-12 km buffer for post-mine creation years, an indication that forest loss declines with an increase in buffer distance.

More than half of the 469 mapped mines in sub-Saharan Africa, according to Ahmed et al. (2021), were established after 2000, with about 200 mines located within 10 kilometres of areas of biodiversity value. This finding aligns with the results of Hund et al. (2017), which indicated that a quarter of operational mines worldwide are situated within a 10-kilometer radius of protected or conservation areas. The expansion and establishment of mines pose severe consequences for conservation and the ecological integrity of forests, involving the encroachment of mining infrastructure into forested land. The construction of roads, railways, and other supporting services further compounds the impact (Hund et al., 2013; Chakravarty et al., 2011; Davis et al., 2020). In SSA, a variety of roads and railways are currently under construction to connect the mines to industries and seaports that are situated several to hundreds of km away (Laurance et al., 2009; Weng et al., 2013). For instance, the Lobito Road corridor, which is a significant transportation network in Central Africa, will connect the copper belt region of the DRC and Zambia to the seaport in Lobito, Angola, cutting through tropical forest (Weng et al., 2013). Addressing the challenges posed by secondary deforestation linked to mining activities in the region necessitates a concerted effort from all stakeholders, including governments, industry players, and local communities. Mine owners and operators need to recognize and assume responsibility for the indirect environmental impacts of their operations, implementing measures to mitigate and offset these effects (Kemp and Owen, 2018). By fostering a sense of shared responsibility and implementing sustainable practices, it is possible to mitigate the environmental threats posed by such activities and work towards a more resilient and ecologically sustainable future (Sonter et al., 2018).

4.2 | ***Impact of Mining Infrastructure on Ecosystems***

The construction and operation of mining infrastructure, such as roads, railways, electricity, and processing facilities, can have significant and often detrimental effects on the surrounding environment. These infrastructures often require clearing large areas of forest to make way for operations and may cause soil erosion, which impacts the integrity of land and soil quality (Ahirwal & Maiti, 2016). This leads to the loss of biodiversity and intact habitat fragmentation and deforestation, with over 1,047 plant and animal species in the International Union for Conservation of Nature (IUCN) Red List impacted by various types of mining globally (Torres et al 2022). Species may lose their natural habitats leading to population decline or even extinction in some cases (Sonter, Ali, & Watson, 2018).

4.3 | *The role of environmental legislation in controlling mining activities.*

Environmental legislation to restrict the negative impacts of mining and promote sustainable practices faces multiple challenges in regulatory adherence and enforcement, with the effectiveness of regulations varying across regions and countries and depending on its stringency (Zulu et al., 2022; Luckeneder et al., 2021; Cabernard and Pfister, 2022). Monitoring this evolving landscape of environmental legislation is essential. In some cases, regulations may be robust, imposing strict requirements on mining companies to minimize environmental impacts. In other cases, the legislation may be less stringent, allowing for more permissive practices. Some countries struggle with regulatory enforcement due to factors such as limited resources, corruption, or insufficient monitoring mechanisms (Edwards et al. 2014; Punam et al. 2017). Other countries adhere to international environmental standards and agreements, which can influence the development and enforcement of domestic legislations related to mining activities.

Environmental legislation of mining can undergo changes over time, influenced by political, economic, and social factors. In some instances, there may be regulatory capture or a shift towards weaker regulations to promote economic development, as evidenced by the frequent examples of protected area downgrading, downsizing, and degazettement (PADDD) to make way for mining. Between 1892 and 2018, 62% of 3,749 PADDD events in 73 countries were to enable industrial-scale resource extraction and development (Golden Kroner et al. 2019). Public awareness, advocacy, and engagement are crucial in holding governments, mining companies and other stakeholders accountable and promoting sustainable mining practices. Advancements in technology and increased transparency can contribute to more effective monitoring and enforcement of environmental regulations in the sector.

4.4 | *Role of Monitoring and Research Limitations*

This study underscores a vital role of applying geospatial techniques and utilisation of available data to explicitly quantify deforestation spatially in sub-Saharan Africa. This approach can guide the monitoring, reporting, and verification of forest changes and carbon loss studies due to mining activities. This study employed matching techniques to compare changes in the forest landscape between treatments and controls (following Sonter et al. 2017), distinguishing it from prior studies that likely overestimated the degree to which mining was a major deforestation driver, by solely quantifying deforestation in the mining locations without comparing them to controls (Merem et., al 2017; Nzunda 2013). For instance, Merem et al. (2017) suggested that 265 km^2 of deforestation in Bukuru, Nigeria, was driven by mining between 1975 and 2005, but this area represents 9% of all deforestation (i.e. 2,992 km^2 more deforestation in treatment than control) that we detected up to 10 km from mines across the whole of sub-Saharan Africa. Unlike previous studies focused on a single commodity (e.g., gold; Alvarez-Berrios & Mitchell Aide, 2015; Swenson et al., 2011; Sonter et al 2017), this research covers mines for all types of commodities mined in sub-Saharan Africa (bauxite, diamond, gold, iron, copper, and limestone, among others), enabling a more holistic assessment of deforestation risks. A major remaining question is how the type of commodity mined alters deforestation, which may be expected given that different commodity classes (e.g., low-value, high-bulk vs high-value, low-bulk) require different infrastructures (Werner et al., 2019).

This research has four core limitations. First, there was a lack of comprehensive data on most artisanal and small-scale mines (ASM), yet these are major components of mining for some commodities (including diamond and gold; Klubi et al., 2018; Lobo et al., 2016), potentially influencing the overall understanding of deforestation patterns associated with mining. Second, challenges arose in utilizing proximity to roads as a covariate in the matching analysis. The inadequacy of road data, considering the vast scale of the region under study, may have impacted the precision of the analysis concerning the role of roads in influencing deforestation patterns. Third, we recognize the limitation of satellite data in identifying mining operations conducted beneath the Earth's surface. Consequently, the study concentrated its assessment on primary and secondary deforestation resulting from open-cast mines, as these are more readily distinguishable using satellite imagery. Fourth, external factors, such as changes in government policies, economic conditions, or technological advancements, are potential influencers of deforestation trends. However, these factors were not fully accounted for in the matching analysis, introducing a limitation in comprehensively understanding the multifaceted drivers of deforestation associated with mining activities.

4.5 | *Conclusions*

This study emphasizes mining-induced deforestation as a significant and often underestimated factor contributing to forest loss in SSA, representing a major conservation concern. Strengthening environmental and mining regulations in sub-Saharan Africa is essential to tackle the magnitude of this issue and effectively prevent or mitigate deforestation. In particular, nations and (often international) mine financiers need a well-defined mitigation hierarchy applied to environmental impact assessments that seeks to avoid, then minimize, and as a last alternative compensate (e.g. via offsets) the impacts on forests and biodiversity. Some governments face challenges in delivering such regulation and oversight, in part due to their dependence on mining revenues. This points towards the needs for international funders and consumers to ensure that mine sustainability is appropriately considered at all stages in mine lifecycles. This includes increased efforts for forest restoration, overseen by authorities upon mine closure, to initiate the long-term process of forest regeneration and associated protection of restored former mining areas from other anthropogenic activities.

Collaboration between governments and other stakeholders is vital for promoting sustainable mining practices and forest conservation in SSA. Given the rapid mining expansion, especially by major companies, and inadequate regulatory oversight, stakeholders must better consider biodiversity preservation, protection of Indigenous rights, sustainable land-use planning, and effective environmental law enforcement. Addressing issues related to land tenure, governance, transparency, and equitable benefit distribution are essential for achieving sustainable development and minimizing adverse impacts on local communities and ecosystems in the context of mining-induced deforestation in SSA.

CONFLICT OF INTERESTS

The authors declare no conflict of interest, and no copyright issues with the data sources and documents cited.

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Table S1.

A summary of useful variables used in matching studies of deforestation and their relevance to this study.

Category	Variables	Impact on deforestation	Relevance to this study
Geographic Characteristics	**Elevation**	Lowland is more suitable for Agriculture (Oakleaf et al., 2019; Tegegne et al., 2016; Laurance et al., 2014).	Derived TWI and TPI are two factors that would determine the suitability of the area to agriculture when mining was established.
	Slope	Determinant for land suitability for agriculture, housing, and infrastructure development (Bavaghar, 2015; Ahmadi, 2018; Kayet et al., 2021).	The steeper the slope the less suitable for crop production, similar to TPI,
	Soil type	Soil quality determines its suitability for crop production. This leads to forest loss. (Witcover et al., 2006; Ahmadi, 2018; Kayet et al., 2021).	Not of much significance to this study.
	Distance to roads	Forests nearer to roads are more susceptible to deforestation (Bavaghar, 2015; Laurance et al., 2009; L.S. Ng et al., 2020; Rosa et al., 2013)	An important variable but was not used in this study due to the scale of the study region and the accuracy of data.
	Distance to waterways	Forests nearer to waterways are susceptible to degradation and deforestation (Aleman, Jarzyna, & Staver, 2018).	Not of much significance to this study
	Forest type	Primary and secondary forest may have different	An important variable for comparing rates of forest loss in

Land Use and Land Cover		rates of distortion due to their varied biodiversity richness (J. Barlow et al., 2012; Gardner et al., 2009; WWF, 2021).	various locations, VCF data was used.
	Agriculture	Forestland suitable for agriculture is most likely to be converted (Müller et al., 2012; Laurance et al., 2014).	As a key driver of deforestation, it is a significant variable
	Urbanization	Settlements often expand into forests (Barbier, 2013; Chakravarty et al., 2011; Jianhua & Jr, 2014)	Settlements are most likely to grow towards the forestlands, making it an important variable
Socioeconomic Factors	**Population density**	The growth in population may lead to expansion of settlements into the forests (Potapov et al., 2012; Ferretti-Gallon & Busch, 2014; Morales-Hidalgo et al., 2015).	A key variable used in this study, an increase in population density would lead to the expansion of settlements, agriculture, and infrastructure.
	Poverty levels	The income of people around the forest may decide the fate of the forest as most may resolve to cutting down the trees for economic gains (den Braber et al.,2018; Ferretti-Gallon & Busch, 2014; Lamb et al.,2005; Witcover et al., 2006).	An important variable for comparing how the inhabitants may destroy the forest to earn a living.

	Access to amenities and infrastructure	Accessibility to alternative sources of energy may save the forest from being used as a source of fuelwood and charcoal for domestic uses. (Hosonuma et al., 2012; Sloan & Sayer, 2015; Thompson et al., 2013).	An important variable for comparing the standards of living among settlements, and how it contributes to deforestation.
Environmental Factors	Climate	Continuous change in climate may lead to aridity and subsequent forest loss (Laurance, 1998; Creese & Pokam, 2016).	An important variable for comparing rates of forest loss in different years
	Rainfall	Rainfall patterns may cause drought, prolonged droughts can stress trees and increase their susceptibility to diseases and insect infestations may lead to degradation (Kayet et al., 2021; Nepstad et al., 2008; Müller et al., 2012).	An important variable for comparing rates of forest loss in different years and at various locations
	Temperature	Higher temperatures can increase the risk of forest fires. (Kayet et al., 2021; Nepstad et al., 2008)	An important variable for comparing rates of forest loss in different years and at various locations
	Natural disasters	Earthquakes and landslides can cause distortion in the forests (Sar et al., 2018).	Not a relevant variable in this study

Political and Institutional Factors	Land tenure	Forest on lands with poorly defined tenure rights may lead to deforestation (Laestadius et al., 2015; Ferretti-Gallon & Busch, 2014; Forrest et al., 2015; Tegegne et al., 2016; Geist & Lambin, 2002)	Not a relevant variable in this study
	Government policies	Weak government policies will always lead to illegal activities which causes deforestation (Newman et al., 2018; Hund et al., 2017)	An important variable in measuring how certain policies can have impact over forests
	Protected areas	Forests within protected areas are less likely to be depleted. (Forrest et al., 2015; Mascia et al., 2014; Andam et al., 2008)	An important variable in measuring and comparing the impact of policies and controls over forest

Table S2.

Database of Mines created post-2000 in sub-Saharan Africa (Ahmed et al.2021)

S.No.	MINE_NAME	YEAR_ESTD	LONGITUDE	LATITUDE	COUNTRY
1	Afema mine	2011	-2.9166	5.49213	Ivory Coast
2	Agbaou	2012	-5.23197	6.10372	Ivory Coast
3	Ahafo (Subika) Mine	2003	-2.36707	7.03104	Ghana
4	Ahafo North Mine	2017	-2.28291	7.18676	Ghana
5	Akyem Mines	2013	-1.02656	6.34342	Ghana
6	Alto Cuilo Mine	2008	19.3782	-9.93112	Angola
7	Bakoudou-Magnima	2011	13.1761	-1.94442	Gabon
8	Bakouma	2011	22.8028	5.74765	Central Africa Rep.
9	Balama Mine	2012	38.6597	-13.3099	Mozambique
10	Baluba Mine	2009	28.3366	-13.0483	Zambia
11	Bambari Passendro	2016	20.7278	6.03967	Central Africa Rep.
12	Banfora Mine	2015	-5.37326	10.3825	Burkina_Faso

13	Baomahun Mine	2013	-11.6587	8.41178	Sierra_Leone
14	Baoule Kimberlite Mine	2000	-9.27805	9.14896	Guinea
15	Batouri Mine	2009	14.4143	4.4557	Cameroon
16	Bea Mountain	2011	-11.0926	7.13631	Liberia
17	Bel_Air	2015	-14.3864	10.321	Guinea
18	Belinga Mine	2006	13.2985	1.21134	Gabon
19	Benga Coal Mine	2012	33.6701	-16.1643	Mozambique
20	Benso Gold Mine	2008	-1.89424	5.19746	Ghana
21	Bibemi Mine	2013	14.0464	9.50464	Cameroon
22	Big Hill STL	2000	27.4721	-11.6823	Congo DRC
23	Bimbo Cement Plant	2010	18.5117	4.30974	Central Africa Rep.
24	Bombore Mine	2016	-0.900163	12.22	Burkina_Faso
25	Bondoukou Mine	2008	-2.96816	8.06404	Ivory Coast
26	Bonikro Mine	2008	-5.36823	6.22467	Ivory Coast
27	Boto mine	2015	-11.3747	12.4668	Senegal
28	Bouroubourou	2011	-11.9292	13.2594	Senegal
29	Bulyanhulu Gold Mine	2001	32.4855	-3.22827	Tanzania
30	Buzwagi Gold Mine	2001	32.6717	-3.86167	Tanzania
31	Calonda Mine	2013	20.5033	-8.37413	Angola
32	Camafuca Mine	2014	20.5548	-8.58777	Angola
33	Cassanguidi Mine	2009	21.3117	-7.49738	Angola
34	Chancho Cement Plant	2008	38.724	9.30997	Ethiopia
35	Chirano Mine	2005	-2.37349	6.30599	Ghana
36	Chiri Mine	2008	20.2894	-9.39374	Angola
37	Chirodzi Coal Mine	2011	33.021	-15.9092	Mozambique
38	Dala Mine	2017	20.4108	-9.67211	Angola
39	Dalafin	2015	-11.6366	12.8693	Senegal
40	Damang mine	2011	-1.8422	5.51245	Ghana
41	Dangote - Ndola Cement	2015	28.7779	-13.0251	Zambia
42	Dejen Cement Plant	2008	38.1415	10.1835	Ethiopia
43	Deziwa Mines	2016	25.9339	-10.9734	Congo DRC
44	Dian_Dian	2016	-13.9938	11.1008	Guinea
45	Dikulushi Mine	2006	28.2706	-8.8926	Congo DRC
46	Dikuluwe mine	2007	25.3323	-10.7675	Congo DRC
47	Dire Dawa New Cement	2012	41.847	9.57343	Ethiopia
48	Disele Mine	2009	26.2536	-10.7532	Congo DRC
49	Droujba Diamond Mine	2011	-9.05295	8.57629	Guinea
50	Dugbe Mine	2012	-8.50071	5.09957	Liberia
51	Dukem Cement Plant	2008	38.9199	8.77198	Ethiopia
52	Edikan Ayanfuri MIne	2011	-1.93206	5.95918	Ghana
53	Emmanuel Manganese	2010	28.5456	-14.4532	Zambia
54	Enterprise Mine	2013	25.2372	-12.2409	Zambia
55	Epanko Mine	2013	36.6788	-8.70356	Tanzania
56	Esaase Mine	2017	-1.79335	6.56804	Ghana

57	Etoile (Nzako, Bangana)	2018	22.7332	4.65604	Central Africa Rep.
58	Farim Mine	2017	-15.244	12.465	Guinea-Bissau
59	Fekola mine	2015	-11.3714	12.5343	Mali
60	Fitwaola Mine	2005	27.883	-12.4065	Zambia
61	Forecariah Mine	2012	-12.7031	9.42866	Guinea
62	Fria mine	2002	-13.5882	10.4363	Guinea
63	Frontier Mine	2007	28.4686	-12.7239	Congo DRC
64	Fucauma Mine	2005	21.2002	-7.36975	Angola
65	Gamina Mine	2011	-6.67605	6.96892	Ivory Coast
66	Gangama Mine	2015	-12.3544	7.73077	Sierra Leone
67	Gbaran Gas Plant	2010	6.29771	5.01764	Nigeria
68	Geita Gold Mine	2000	32.1785	-2.87659	Tanzania
69	Gonka Mine	2016	-8.80884	11.1734	Mali
70	Gora Mine	2014	-11.9328	13.3018	Senegal
71	Gounkoto Mine	2011	-11.1963	12.7311	Mali
72	Gourma Mine	2014	0.940687	12.5564	Burkina Faso
73	Grumesa Mine	2017	-1.58079	5.94567	Ghana
74	Hire Mine	2013	-5.26794	6.18812	Ivory Coast
75	Homase Mine	2001	-1.03579	6.16425	Ghana
76	Hounde Mine	2016	-3.49338	11.4736	Burkina Faso
77	Hwini-Butre Mine	2007	-1.88273	4.97066	Ghana
78	Ibese Cement	2012	3.0377	6.99576	Nigeria
79	ITY_Bakatouo Mine	2008	-8.1116	6.87415	Ivory Coast
80	Judeira Mine	2016	27.0646	-11.2238	Congo DRC
81	Kabanga Mine	2013	30.5614	-2.86545	Tanzania
82	Kabolela	2009	26.4792	-10.8452	Congo DRC
83	Kakanda	2009	26.4022	-10.7358	Congo DRC
84	Kalana Main mine	2016	-8.20014	10.7913	Mali
85	Kalia Mine	2016	-11.0239	10.136	Guinea
86	Kaloleni Cement Plant	2007	39.6342	-3.84562	Kenya
87	Kalukundi Mine	2006	25.8896	-10.6612	Congo DRC
88	Kalumbila Mine	2012	25.3051	-12.1886	Zambia
89	Kalus Mine	2003	27.2685	-11.5968	Congo DRC
90	Kamatanda Mine	2014	26.7477	-10.857	Congo DRC
91	Kamoa Mine	2014	25.0945	-10.6278	Congo DRC
92	Kango Nort mine	2014	10.185	0.52492	Gabon
93	Kansanshi Mine	2004	26.4302	-12.1045	Zambia
94	Kansuki Mine	2011	25.9217	-10.7991	Congo DRC
95	Kapulo Mine	2016	29.2308	-8.29836	Congo DRC
96	Kariba Amethyst Mine	2009	26.8868	-17.7014	Zambia
97	Kasala Mine	2017	27.4552	-11.163	Congo DRC
98	Kayelekera Uranium Mine	2009	33.7076	-10.0037	Malawi
99	Kibali Mine	2013	29.6028	3.12273	Congo DRC
100	Kileba Mine	2014	27.1256	-11.2844	Congo DRC

101	Kiniero	2002	-9.80408	10.4258	Guinea
102	Kinsenda Mine	2002	27.9676	-12.2557	Congo DRC
103	Kinsevere	2002	27.5691	-11.3636	Congo DRC
104	Kipoi mine	2014	27.1019	-11.2504	Congo DRC
105	Kitotolo mine	2016	27.3945	-7.32194	Congo DRC
106	Koba Mine	2014	-13.4153	11.3017	Guinea
107	Kobada Mine	2015	-8.59469	11.6283	Mali
108	Kodieran mine	2013	-8.22432	10.8429	Mali
109	Koidu Mines	2003	-10.9707	8.62714	Sierra_Leone
110	Kokoya mine	2006	-9.27344	6.63204	Liberia
111	Koumba Mine	2007	11.9797	-1.81765	Gabon
112	Kouroussa	2009	-9.85753	10.678	Guinea
113	Krakama Oil Field	2017	6.89713	4.55079	Nigeria
114	Kribi Mine	2009	9.8947	2.78065	Cameroon
115	Kubi (Betanase) Mine	2016	-1.72677	6.00772	Ghana
116	Kwale Mine	2011	39.4453	-4.3914	Kenya
117	Laurica Diamond Mine	2003	21.0472	-8.28691	Angola
118	Lauzoua Mine	2006	-5.39034	5.32117	Ivory Coast
119	Lero_fayala	2015	-10.0492	11.7444	Guinea
120	Longatshimo River Mine	2007	20.9544	-6.87647	Congo DRC
121	Lonshi Mine	2001	28.9403	-13.1753	Congo DRC
122	Loulo Mine	2009	-11.4036	13.0577	Mali
123	Lubambe Mine	2012	27.7634	-12.3185	Zambia
124	Lufukwe Mine	2012	27.9796	-9.55009	Congo DRC
125	Luilu Mine	2006	25.3828	-10.6921	Congo DRC
126	Luita mine	2009	26.313	-10.7601	Congo DRC
127	Lukenya Cement Plant	2010	37.0478	-1.49694	Kenya
128	Lulo Mine	2003	18.8411	-9.57044	Angola
129	Lumwana Mine	2011	25.8627	-12.2812	Zambia
130	Luo Camatchia Camagico Mine	2005	20.4664	-8.96978	Angola
131	Maamba Coal Mine	2009	27.1935	-17.3499	Zambia
132	Magna_Egoli mine	2001	-11.2119	8.69714	Sierra Leone
133	Mambere River Mine	2008	15.4268	5.12877	Central Africa Rep.
134	Mana (Wona Kona, Siou, Fofina) Mine	2008	-3.42239	11.9919	Burkina Faso
135	Mandala Diamond Mine	2009	-9.32881	8.79955	Guinea
136	Manica Mine	2002	32.9351	-18.9139	Mozambique
137	Mankranho Mine	2017	-2.13597	7.88257	Ghana
138	Marampa Mine	2011	-12.5079	8.68259	Sierra_Leone
139	Marropino Tantalum Mine	2012	37.9052	-16.5092	Mozambique
140	Mashamba West	2007	25.3913	-10.7465	Congo DRC
141	Massawa	2018	-12.0365	12.9645	Senegal
142	Mbakaou Mine	2014	12.9411	6.9215	Cameroon
143	Mbalam-Nabeba Mine	2007	13.9504	2.22339	Cameroon
144	Mbeya Cement Plant	2007	33.2271	-8.92976	Tanzania

145	Melka Jebdu Cement Plant	2011	41.7841	9.6061	Ethiopia
146	Melut Oil Field	2003	32.34	10.5571	South Sudan
147	Mfamosing Cement Plant	2009	8.51492	5.06375	Nigeria
148	MIBA Mine	2002	20.6641	-6.17384	Congo DRC
149	Misisi Mine	2014	28.7265	-4.76552	Congo DRC
150	Mkushi Copper Mine	2010	29.1403	-13.9459	Zambia
151	Moatize Coal Mine	2011	33.7849	-16.1662	Mozambique
152	Mobilong Mine	2013	15.3096	3.32925	Cameroon
153	Mofe Creek	2017	-11.1415	6.88645	Liberia
154	Mojo Cement Plant	2010	39.0997	8.55033	Ethiopia
155	Moma Titanium Mine	2007	39.6403	-16.5299	Mozambique
156	Mombasa Cement Plant	2007	39.7156	-4.01041	Kenya
157	Monts de Cristal Mine	2007	10.281	0.449778	Gabon
158	Morila mine	2000	-6.84488	11.686	Mali
159	Morrua Tantalum Mine	2000	37.8699	-16.2756	Mozambique
160	Mount Nimba	2012	-8.37082	7.6613	Guinea
161	Mtwara Cement Plant	2015	40.0445	-10.2586	Tanzania
162	Mufulira (Mopani) Mine	2000	28.2234	-12.4941	Zambia
163	Mugher Cement Plant	2015	38.3419	9.42459	Ethiopia
164	MUKONDO MINE	2009	26.3522	-10.7247	Congo DRC
165	Muliashi Mine	2012	28.3164	-13.0644	Zambia
166	Murowa Diamond Mine	2004	29.9158	-20.5354	Zimbabwe
167	Musonoi Mine	2007	25.4417	-10.7188	Congo DRC
168	Musoshi Mine	2009	27.7256	-12.269	Congo DRC
169	Mutanda Mine	2010	25.8364	-10.7842	Congo DRC
170	Namoya Mine	2012	27.5445	-4.02971	Congo DRC
171	Nampala mine	2014	-6.21831	11.1546	Mali
172	Natougou Mine	2016	1.4057	12.004	Burkina Faso
173	Nayega Mine	2017	0.433602	10.7437	Togo
174	New Liberty Mine	2015	-11.136	7.00473	Liberia
175	Ngovayang Mine	2010	10.7294	3.49384	Cameroon
176	Nhamucuarara Chua	2008	32.7905	-18.904	Mozambique
177	Nkamouna Mine	2014	13.839	3.28225	Cameroon
178	North Mara Mine	2002	34.5031	-1.47516	Tanzania
179	Ntotoroso Mine	2016	-0.394551	5.78073	Ghana
180	Nzema Mine	2011	-2.24558	5.00675	Ghana
181	Obajana Cement	2007	6.43598	7.99519	Nigeria
182	Obu/ Okpella Cement Plant	2017	6.40097	7.35631	Nigeria
183	OJVG Sabodala	2010	-12.0927	13.1298	Senegal
184	Owere Gold Mine	2011	-1.16905	6.6849	Ghana
185	Pagala Mine	2000	0.851337	8.21863	Togo
186	Palouge Oil Field	2003	32.4813	10.4429	South Sudan
187	Pampe Mine	2006	-2.12914	5.64812	Ghana
188	Pepel Mines	2001	-13.0635	8.58657	Sierra Leone

189	Port_Loko Mine	2016	-12.8152	8.78	Sierra Leone
190	Putu Mine	2014	-8.23234	5.71445	Liberia
191	Rwinkwavu Mine	2008	30.594	-1.97518	Rwanda
192	Sabodala Mine	2008	-12.1217	13.1977	Senegal
193	Salamanga Cement Plant (	2012	32.6529	-26.3946	Mozambique
194	Scantogo Mines	2014	1.54785	6.5948	Togo
195	Simandou	2013	-8.88697	8.49024	Guinea
196	Siribaya Mine	2016	-11.2163	12.4011	Mali
197	Sissingue Mine	2017	-6.19895	10.4321	Ivory Coast
198	Somiluana Mine	2006	21.1675	-8.20428	Angola
199	Southern Togo	2015	1.52172	6.47679	Togo
200	Syama Mine	2009	-6.06088	10.8022	Mali
201	Synclinorium Mine	2018	28.2055	-12.8451	Zambia
202	Tabakoto Mine	2006	-11.19	12.9459	Mali
203	Tazua Mine	2009	18.1349	-9.27058	Angola
204	Tchibanga Mine	2015	11.3876	-3.39495	Gabon
205	Tchiuzo	2014	20.3398	-9.20777	Angola
206	Teberebie Mine	2000	-2.03792	5.26561	Ghana
207	Telimele Mine	2017	-13.271	10.8207	Guinea
208	Tenke-Fungurume	2009	26.1787	-10.5816	Congo DRC
209	Thar Jath Oil Field	2002	30.1328	8.72051	South Sudan
210	Tongo Mine	2006	-10.9936	8.24782	Sierra_Leone
211	Tongon Mine	2010	-5.70736	9.93293	Ivory Coast
212	Tonguma Mine	2015	-11.0544	8.22963	Sierra Leone
213	Tonkolili mine	2013	-11.6816	8.98851	Sierra_Leone
214	Topa Mine	2016	20.6462	6.04471	Central Africa Rep.
215	Tshikapa River Mine	2015	20.7567	-6.48528	Congo DRC
216	Tulawaka Gold Mine	2005	31.5411	-3.20994	Tanzania
217	Twangiza Mine	2011	28.7418	-2.87097	Congo DRC
218	Unity Oil Field	2002	29.6776	9.46028	South Sudan
219	Yanfolila mine Gonka	2016	-8.40587	11.2118	Mali
220	Yaramoko	2014	-3.27469	11.7553	Burkina Faso
221	Yatela Mine	2001	-11.75	14.0879	Mali
222	Yekepa Mine	2012	-8.50878	7.5239	Liberia
223	Youga Mine	2008	-0.465288	11.1012	Burkina Faso
224	Zambezi - Ndola Cement	2009	28.7187	-12.9725	Zambia
225	Zogota	2012	-9.09678	7.98129	Guinea

Figure S1.

Love-plots from standardized mean difference output for countries used in the Nearest neighbor matching by country.